Performance Evaluation in Computing With Words

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Abstract

We propose a theoretical background and a computational technique that evaluates the performance of systems of natural language processing. The system of our interest analyzes natural language texts (narratives of the questions presented by the analyst, and narratives of the sources, i.e. relevant documents), and generates new texts under various focus of interest (the *meta-intent*) and with various degree of compression. The narrative of the questions serves the purpose of determining the meta-intent and the required degree of compression. This is an equivalent of the set of goal, purpose and/or command that arrives from the upper level in any large complex system. The narratives of the sources can be considered the totality of the Elementary Loop of Functioning. It can have many levels of resolution, too. The engineering object of analysis is a software package whose inputs are a) the question, b) general information related to the analyst's foci of interest, and c) the set of sources (natural language texts). The products at the output are "action items": the list of recommendations. In many cases, it includes: a) the answer to the original question, and b) the knowledge structure that incorporates knowledge from the processed sources. Both parts of the output are natural language texts, too. The purpose of this analysis is evaluating the quality of the result.

Keywords: action, actor, behavior generation, compression, corpora, document, ELF, interpretation, knowledge representation, narrative, natural language, object of action, summary, summarization, text processing

1. Introduction

Unlike many existing devices for goal oriented text generation, the overall system of our interest employs mechanisms of a) constructing the architecture of knowledge contained in a particular text, and b) subsequent use of this architecture for constructing texts representing this knowledge with the desired degree of compression. The system learns from experience because its knowledge structure incorporates everything it learned from the sources and from the questions. The validity of knowledge can be judged by a human operator.

The processes of extracting relevant information from natural language documents require constructing an adequate knowledge organization based upon multiple sources. We believe that a meaningful interpretation of an analyst's question is possible, too, only within a framework of a particular knowledge structure (which might be different from the knowledge structure built upon the sources). Thus, the hub of our efforts is situated in construction of proper knowledge structures. We build them following the conceptual paradigm of the multiresolutional approach. Especially effective are our multiresolutional techniques of disambiguation, as related to the elements of natural language texts. The validity of disambiguation can be judged by the convergence of the processes of disambiguation.

The special advantage of our method and software package is that it builds up a knowledge representation and learns additional knowledge from each new text submitted. This new knowledge is used for the subsequent compression of texts even if it has not been directly represented in the expected sources: every new text of a particular domain is being compressed by a "more knowledgeable" package. These new texts generated by the system are the answers, and the "density" of the answer depends on the request of the asking analyst. Method allows for processing not only single texts, but also groups of texts. It can answer questions, groups of questions, refine questions, and disambiguate answers. It allows for preparing surveys, and maintains topic-oriented and context-oriented knowledge bases for a variety of decision support needs. The quality of decisions judged by the result of applying these decisions.

2. The Concept of the System for Processing the Questions and the Set of Sources

The Problem of Knowledge Extraction and the Problem of Text Compressing. Extraction of knowledge from texts seems to be of crucial importance for solving the problem of synthesizing the proper answer if the question is submitted and the sources of knowledge are available in the form of natural language texts. The skills of *abridging, summarizing, abstracting and surveying* are highly important for solving the problem of question answering. People are doing all these things intuitively and often fail. They tend to overemphasize trivial passages and overlook hard to infer connections hiding potential breakthroughs. They focus upon particularities and losing the larger picture. Obviously, the *text* of the document is not equivalent to the *knowledge* that is conveyed by this document, not to speak even about its *meaning* that for the same text can be different in the different *contexts*. There is no clear definition for "meaning" because there is no single way of conveying the content, thought, emotion or even a mood by using the arsenal of natural language. Currently, the meaning is judged by the human operator.

Until recently, the process of question answering was usually done by humans-experts. They "extract meaning" and "summarize" intuitively, they "survey" multiple sources based upon their instinct of relevance and their skill of generalization. If the multiple text bundling is required, of if the text compressing should be performed, people rely upon experts. When we need to use experts, and to make their labor less expensive, we often employ experts' "natural" ability to quickly compose answers, summaries, and surveys. (The terms "abridged," "compressed," "condensed" are typically understood as "summarized"). The summary of the situation, actually represented in a thoughtful answer to a fuzzy question, should give an abridged image of the essence of knowledge contained in the document. The need in the condensed "knowledge" contained in the document demonstrates our need in the meaning of this knowledge and in the validation of the results of knowledge processing..

The Existing Efforts in Joint Processes of Knowledge Compression and Question Answering (KCQA). KCQA is, in fact, the essence of the answering a question of a very vague type: "What this article (or a set of articles) is all about?" Thus, the question-answering process in numerous cases can be divided in two interrelated stages:

Stage 1. Find a package of sources relevant to the question, and

Stage 2. Categorize them, i. e. formulate, what this set of sources is all about.

It is not difficult to demonstrate that additional stages can produce further focusing of attention and end up with the regular paradigm of asking-answering. The bottom line will always be in searching for a relevant subset of sources and generating a text that could be considered a compression of the set of sources for question answering, i.e. KCQA. The latter is required in many domains starting with business of publishing and ending with funding agencies that are swamped by the overly long descriptions which should be understood and responded to. Again, an expert is the only hope. The art of summarization has not been yet formalized so that we could learn it, teach it and even more, to delegate summarization to a computer.

The existing efforts in summarization are oriented toward receiving nicely looking short statements of contents, abstracts, or summaries by the virtue of imitating prior results in summarization (the superficial "tokens" of a good summary are used). The efforts in discovering the essence of a text are dealing with the most intimate component of human information processing. Well known rules of thumb like "use first paragraph of an article as its summary" rely upon a frequent maxim of newspaper reporters to use the first paragraph as an abstract. However, in most of realistic cases this maxim fails. Usually, the intention to mimic human activities automatically lead toward cryptic, garbled, almost illegible documents where subtitles, titles of the figures, and bulletized statements are mixed together. This happens because there is no method of telling the significance of one sentence from another from the point of view conveying the meaning.

The system with KCQA employs a method of "knowledge structuring," "text compression," and even "meaning extraction" that would outline the steps of text analysis and text generation leading toward a harmonious document which could be easily understood and practically applied by the end user. In our product, text processing is based upon visualizing the structure of knowledge contained in a text as a multiresolutional web (or multiresolutional network) of text units. In order to understand the method, some preliminary information should be acquired and taken in account so that we won't need to go to the expert for explanation of words "knowledge" and "meaning" (see [1, 2]).

Novel text processing tools outlined in this paper have been developed by Cognisphere, Inc. They allow for pursuit of the meaning during the multiresolutional decomposition of the sets of texts. The *meaning explication (or discovery)* processes can be totally independent ("thesaural meaning") and can be guided by an assignment, bias, context, etc. The package developed by Cognisphere relies upon techniques for constructing the architecture of a text based upon the concept of multiresolutional text decomposition and aggregation. This concept presumes that entity-relational networks (ERNs) constructed for more simple (higher resolution) units of text are nested in more complicated units that can have a separate label.

The simplest and the most practice oriented outcomes of this development are the new tools for text compression and new text generating algorithms that can be applied in a multiplicity of the areas: for question answering, for summarizing documents, papers, books, for preparation of brief reports of meetings, for document searching in the large document bases and on the Web, and many others. This implies that the network constructed at high resolution can be substituted by a generalized but computationally simpler network constructed at lower resolution if the groups of high resolution ERNs will be considered a lower resolution units and even might be substituted by separate labels. Similar consideration can be applied to the lower resolution network and even lower resolution units can be constructed. If this process is recursively repeated bottom-up, a hierarchy of representation is obtained.

The development of compressed documents by humans is frequently considered a guesswork. In the available examples of automated summarization, the emphasis is done upon creation of a new, shorter document which will include some elements of the initial text considered its milestones: highlighted words and phrases, frequently used sentences, subtitles, pieces of the tables of contents, and so on.

The results are mostly unsatisfactory and often, very disappointing. Indeed, the summarization software packages produce at their outputs garbled texts which require strong editing - at best. As a result, all leading companies, searching the Web, have practically abandoned meaning-oriented summarization. They use "token-driven" summarization: they extract several lines from the beginning of the document, or a list of sub-titles, and so on, to give the user some hint about the text.

Joint Decomposition and Compression as Parts of General Text Analysis. The meaning-oriented text compression (e.g. summarization, or abstracting, or extracting the essence) is a sub-task of a more serious problem: to perform the text transformation and analysis that would organize the text in a system of generalized units without sacrificing the contents. We are talking about constructing *a multiresolutional system of knowledge representation* for a particular text. This can be done only by *generalizing* and subsequently, *contracting (consolidating, encapsulating)* the descriptions that are wordy and contain details of the second order of importance. Apparently, a device for the text compression should be capable of distinguishing the first order of importance (with larger, or coarser "granules" of the text) from the second order (with smaller, or finer "granules").

The term "granule" here is equivalent to the ERN unit that "has a separate meaning" and can be substituted by a separate label. By constructing granules of high resolution, then of lower resolution and so on, one performs consecutive bottom-up generalization of the text. Certainly, such generalization is different from the mechanical text filtering. It presumes constructing a new, generalized text by using words and expressions that not necessarily are the part of the document under consideration. It presumes substitution of the detailed description by metaphorical "short-hand" passages, and/or metonyms.

As a result of summarization, the user is supposed to discover within the texts the units of meaning that might be hidden *even from its author*. This can be done by putting it in a perspective of other texts which might be of interest for the user but are not necessarily known to (or taken in account by) the author. This is where the efforts in compressing the text gradually demonstrate their closeness to other important jobs in of text processing which are extremely time consuming and at present rely solely on human expertise.

It would be prudent to say that the consecutive bottom-up generalization is not a discovery of the author. The problem of compressing (abridging, generalizing, surveying, summarizing) a set of diverse statements, or documents and determining their joint meaning is well known. This problem is presently unsolved. The specifics of our approach is bundling together a multiplicity of related problems based upon similarity that can be found in their essence. Many additional jobs can be included in the problem as we visualize it. For example: development of the *group platform* of the associated documents demonstrating elements of similarity as far a particular situation is concerned. The group-platform problem is equivalent to a core problem of text processing for decision support systems.

The Central Concept of MR-Text Processing. When we are talking about text decomposition, we do not refer to the standard formal procedure of text parsing, a procedure which could rely on syntactic analysis. Certainly, the existing algorithms of syntactic parsing can be improved, some new algorithms of parsing can be created, the results of parsing can be taylored to multiple practical applications by using sets of rules which allow to notice new "tokens" of importance. These efforts for improvement parsing algorithms are very important, but they are incapable of solving the problem of *text compression via knowledge generalization, knowledge discovery,* and *knowledge mining.* In this paper, we rely on a software package that is capable of recognizing new units of knowledge that have a meaning corresponding to the meaning requested within the assignment for text processing.

Several new scientific developments are applied in this software package. One of them is a metonymic combinatorial text transformation. We employ a "multi-granular" organization of combinatorially constructed metonymic units of texts. This approach is based upon formation of the metaphors constructed via text generalization. We believe that this is potentially the most powerful mechanism of the text contraction. Finally, analysis of the structural loops gives an opportunity to discover among them the dynamic units containing new meaning.

The method is especially promising because it uses the same structure of information processing no matter what is the information medium: text, visual images, audio, etc. As the need in multimedia processing is growing, our package allows the uniform solution that can be used for improving convergence in the processes of disambiguation described later. The procedure of constructing the representation of REALITY (natural languages, visual images, audio information, physical reality) is described in [1, 2]. Entities to be encoded, put in correspondence as ERN and interpreted exist in REALITY but are not recognized and encoded.

An intelligent (human based, or automated) classifier should recognize and encode the entities. This requires transforming information into a perceivable carrier (signal). The signal inputs the system. Initially it is perceived as a "chaos." The subsequent classification is performed within the intelligent observer (our software package). Within the input chaos, the observer perceives a multiplicity of zones of with various degrees of uniformity. The observer groups them into different classes. The sets of different classes of uniformity can be thought of as singularities by themselves. Thus, the singular zones of signal uniformity in addition to singular entities are determined as a result of perception. Then, the resolution of classes distinguishing is increased, the scope of dealing with input information is reduced. What was "uniform zones" gives an opportunity to produce its further classification. The whole host of singular objects is informationally reorganized, too. As a result, new sets of objects are formed pertaining to new level of resolution. The process continues top-down. At each level of resolution there are additional singular objects: those, that has not been noticed during previous grouping processes because of their low resolution. These "left-out" entities supplement the multiresolutional system of entities that has been received. After this, a new iteration of grouping is supposed to be performed at each level of resolution[1].

The system of singular objects by itself is not sufficient for interpretation. At each level of resolution a loop of closure should be defined to perform the process of interpretation. All components of semiotic analysis (syntax,

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[1] The process can be made more understandable by the following clarification: the entities that contain a meaning have more than one element: they contain information about an acting object (an ACTOR), about the ACTION produced by the ACTOR, and about the OBJECT upon which the ACTION was extended. Many entities containing experiential knowledge of this sort allow to make a generalization about a preferable rule of action in a variety of recorded situations. Thus, entities can be grouped into the *experiential* and the *normative* statements (the latter are called *rules*).

semantics, and pragmatics) should be put in correspondence with the elementary loop of functioning (ELF) defined by the closure at a level of knowledge representation [1, 2].

The circulation of knowledge within ELF is done by the virtue of communication which changes the incarnation of knowledge from a node to a node passing through the stages of encoding (in SENSORY PROCESSING), representing and organizing (in WORLD MODEL), evaluating (in VALUE JUDGMENT), interpreting, anticipating, intending, and planning (in BEHAVIOR GENERATION), generating (in ACTUATORS), applying (in the WORLD), and transducing (in SENSORS)—all considered as different forms of communication (mappings from one language to another). As something happens in the World (discourse, set of texts, additional document arrived, additional AUDIO was submitted, etc.), it is transduced by sensors into an appropriate form and the process of representation begins. The role of Perception is to represent the results of sensing in some organized manner using *signs*. This process of shaping up the organization is called Syntax. It starts at this point, it continue at all subsequent stages of dealing with Knowledge while it is more and more generalized. The initial structure becomes Knowledge as the latter gets more and more generalized so that after representation is completed, interpretation is possible. Interpretation enables the process of Decision Making including Planning within the module of Behavior Generation in which Semantics joints Syntax to create the *interpretant*.

The interpretant materializes in the process of Actuation, which is analogous to generation of new knowledge and then, in a new text. As a result of this process new Narrative arrives into the World, creates changes in the World — physically and/or conceptually. New *objects* emerge; they can be of physical and/or of linguistic nature. The sensors change their output signals and the new cycle starts of the loop of closure.

The successful functioning of the loop dwells upon creativity of Decision Making processes in the module of Behavior Generation. The hypotheses enter the subsystem of Behavior Generation as a substitute for the rules, the decision for an action is made, the action is performed, changes in the world occur, the transducers (sources of information) transform them into a form that can be used by Source Code Processing units, and the long and complicated process of moving from signs to meaning starts again. Now, the enhanced set of experiences presented in the text brings about another hypothesis that can confirm or refute the tested ones. This is when the *symbol grounding* happens.

After multiple tests, the hypotheses can cross the threshold of "trustworthiness" by constantly exercising symbol grounding, and a new rule is created. Further generalization of a rule (or a set of rules) within a particular context is considered to be "a theory". At each step of this development, the unit under consideration undergoes a comparison with other kindred units confined in corresponding databases (of Experiences, of Rules, and of Theories). Then the symbols tentatively assigned to some "unities", "entities", or "concepts" enter their place within the database of concepts (which is a relational network of symbols).

3. Texts Analysis: Decomposition and ERN Construction

Each unit of the text carries its meaning that should be interpreted within the part of context belonging to the ELF at a particular resolution. The hierarchical decomposition of context assignment is presumed. The domain assigns the context to the document (i-th level), the document in turn (within the overall domain) assigns the context to its sections ([i-1]-th level). The section (together with the whole document) assigns the context to its paragraphs. The paragraph and its neighbors-paragraphs assigns the context to its compound sentences (CS). The CS (together with other sentences around) assigns the context to its simple sentences (SS). Each SS (jointly with other SS and CS of the paragraph) assigns the context to its smaller scale components (SSC_i, I=1, 2,…). Each SSC (of this particular SS and other SS and CS of the vicinity of attention) assigns the context to its smallest SSC-units called M-seeds (the seeds of meaning).

Each M-seed (together with its neighbors) conveys the context to its words (2nd level), and each word (and its neighbors) conveys the context to its parts (1st level). We can see that the text becomes a multiresolutional ERN (entity-relational-network) which can be considered a web with interrelationships of belonging and contextual influences. This web carries meaning and interpretation and should be discovered and processed. A measure of significance can be assigned to all units of text.

This measure is called "value of significance" and is based upon the size of the unit, frequency of occurrence in the text and the quantity of associative links with other units in the text.
This measure directly affects the quality of results. The following stages perform the preliminary text analysis and transform the narrative of the input natural language text into the multiresolutional hierarchy of knowledge representation.

Stage A1. Consecutive decomposition of the narrative into the nested multiresolutional system of ERNs. A system of tokens was developed based upon conducting consecutive decomposition of English texts.

There are evidences that similar tokens can be developed for other languages, too. The system is similar to the one utilized for visual images and is adequately represented by Figure 1.

Stage A2. Top-down and bottom-up conducting of the process of *disambiguation* (see [3])which is supposed to end-up at each level of resolution either by converging or by generation of an inquiry in the form of a question or additional text request.

Disambiguation procedures are based on libraries of rules that reflect the formation of gestalt-routines known for a particular domain of activities and/or discourse. It is based upon formulating hypotheses and verifying them at the adjacent levels below and above [3]. We have developed a package of rules for a linguistic disambiguation for a particular type of activities (e. g. summarization). Since the premises are general, similar set of rules can be developed for other assignments, too. The loops of disambiguation exercise simulation of applying at levels (i+1) and (i-1) the function that was hypothesized at the i-th level (see Figure 2).

Stage A3. Putting in correspondence the result of Stages 1 and 2 with the knowledge architecture of the domain of interest; tracing the initial narrative within the joint knowledge architecture. Thus, within the same multiresolutional architecture, a multiplicity of various texts (narratives) can be represented by corresponding strings of pointers without changing the architecture.

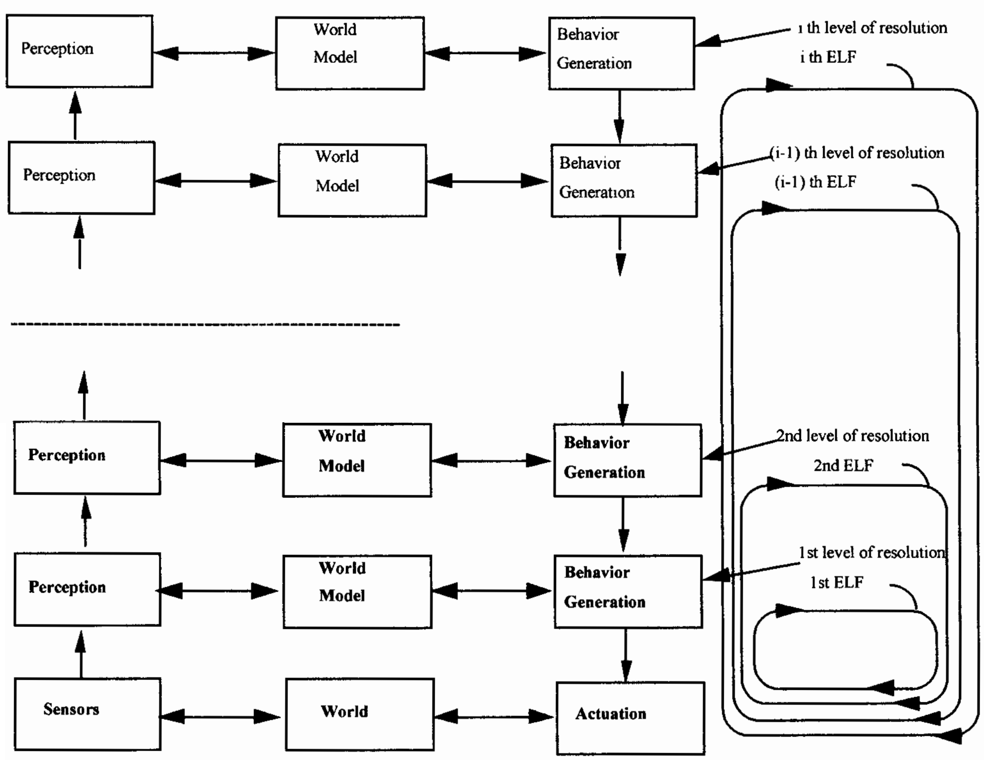
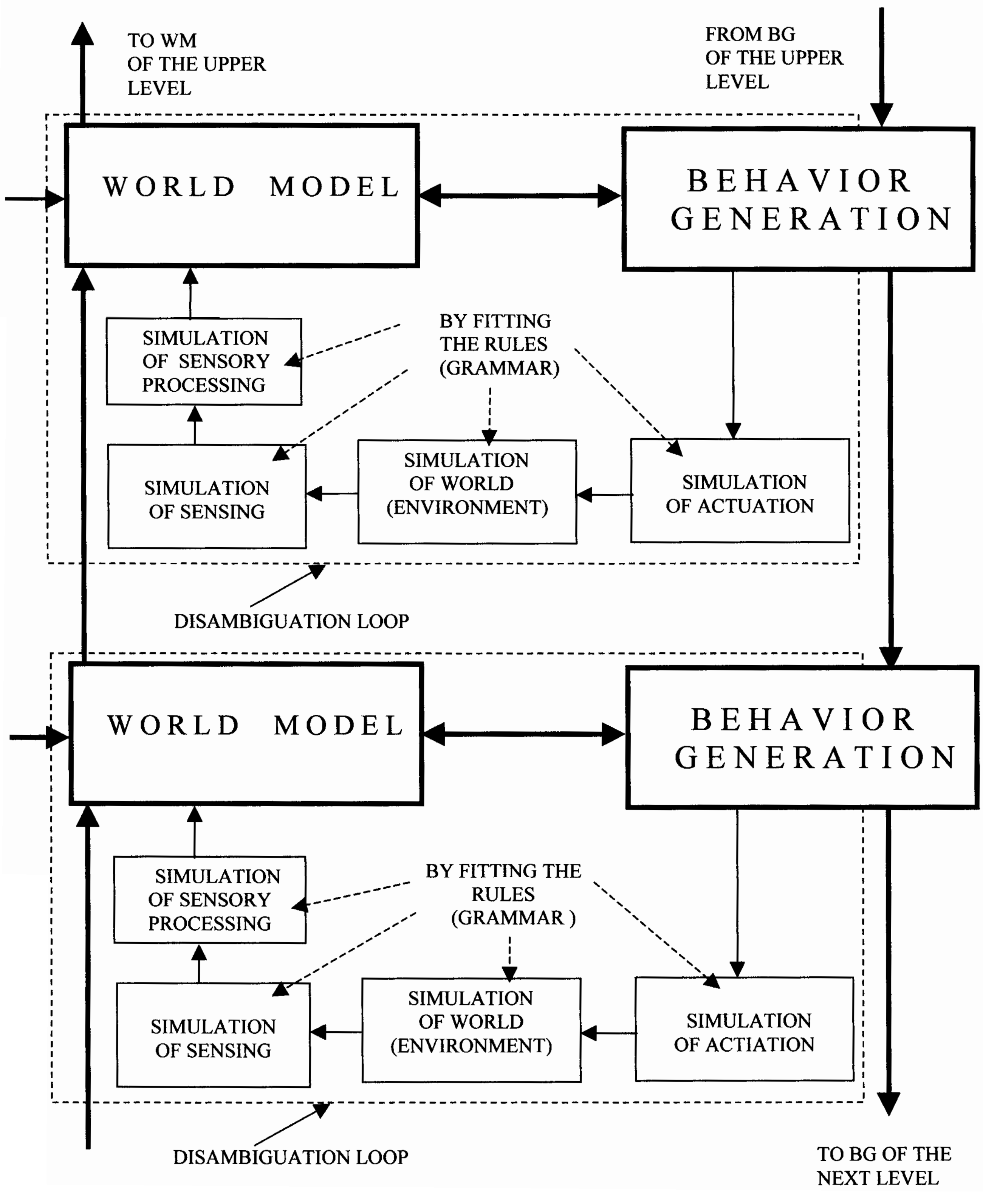


Figure 1. Multiresolutional text organization

Figure 2. Multiresolutional processes of disambiguation



As these three stages are completed, the multiresolutional ERN knowledge base is considered to be constructed.

4. New Text Generation: How Do We Receive the Answers

This multiresolutional ERN knowledge base is used for new text generation under a multiplicity of particular assignments: e.g. to construct summary, abstract, abridged text, summary upon the multiplicity of texts, survey of multiple documents, etc. The idea of new text generation is based upon the opportunity of constructing most probable ELFs out of available components.

The following stages should be performed for the new text generation:

Stage G1. The level of resolution are to be selected at which the expected text should be generated. Sometimes, the particular indications are given that determine the user's preference toward chosen particular aspects of the domain of discourse. In these cases, the values of significance are increased correspondingly for related units stored in the knowledge base. The pointers for tracing the narrative at this level are enabled, and the output text is generated by following the string of these pointers as shown for Stage G2.

Stage G2. The pointers are followed and the narrative is generated. The richness of detail of the output is determined by the levels of resolution selected for text generation. This procedure invokes several rules of text generation that allow for associating simple sentence components (SSC) with Actor, Action and Object of Action. These rules should be applied either prior to text generation or as a part of its process:

a) Generation of Generalized SSC_i

In all sentences, substitute SSC_i (or n units of SSC_i) for the GL-SSC_I (generalized label SSC_i) Replace the whole SSC_i with its generalized label, in a manner such that it's possible to go back (to recognize, what was in place of generalized SSC_i label and substitute it back to the original set of words).

b) Generalized SSC_i Clustering

Group together simple sentences with the same Generalized SSC_i. The clusters of Generalized SSC_i should be marked by their relative location in the sentence.

c) Categorizing the SSC_i Clusters

Recognize the groups of Generalized SSC_i Clusters related to actors, objects of action and actions. The groups should be marked by their relative location in the sentence and form an ERN.

d) Mergers within the Action related SSC_i Clusters

For a cluster of Action related groups, check against significant M-seeds on intersections. Temporary unify intersecting clusters, mark their relative location in the sentence.

e) Mergers within the Actor related SSC_i Clusters

For a cluster of Actor related groups, check against significant M-seeds on intersections. Temporary unify these clusters, mark their relative location in the sentence.

f) Mergers within the Object of Action related SSC_i Clusters

For a cluster of Object of Action related groups, check against significant M-seeds on intersections. Temporary unify these clusters, mark their relative location in the sentence.

f) Construct graphs for all resulting sentence structures for visual analysis

(An easily interpretable example of the graph is demonstrated in Figure 3)

g) Order the Graph as the Original Text Flow

Conduct permutations: start with arranging with Actor related SSC, follow with object of action related SSC, make intervals for permutations required (if necessary). Different graphs will be obtained for different size of the M-seeds and for different value of significance of them. The quality of the newly constructed ELFs is determined by the values of probability the new ELFs entail at all levels of resolution.

Using the ELF-based Activity Graph. The graph is a powerful additional tool for conducting the text interpretation. In the package by Cognisphere, the following opportunities of using the graph representation are exercised for the compressed texts generated at the output:

• Read the flow of connections from left to right by using balloons, or a window for displaying alternatives.

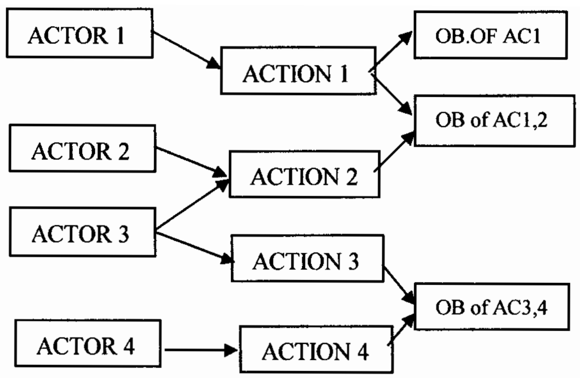


Figure 3 Graphs of Output Formation

• Request for evaluation of probabilistic validity for the triplets Actor-Action-Object of Action.

Transform the Graph into Text to be Generated. The process of transformation comprises the following steps: a) substitute all SSC_i by their original sets of words from the original text; b) sequence the sentences along (parallel) with the original text pointers tracing; c) sequence the sentences along with the original text pointers tracing; d) form paragraphs when the adjacent sentences do not intersect. The software package uses a proprietory set of rules for Output Text Generation; the rules are taken from the human experience of text analysis. Some examples of rules are given in this list:

- When two consecutive phrases have the same Actor and the number of words in their Action SSC_i exceeds that of the joint number of words in [ActionSSC_i + Object-of Action SSC_l] then unify them into one sentence with the structure: Actor SSC_i + (Action SSC_I + Object-of-Action $SSC_i)_1$ + (ActionSSC_i +Object-of-Action$SSC_i)_2$
- When two consecutive phrases have the same Object-of-Action SSC_i and the number of words in this Object-of-Action SSC_i exceeds that of the joint number of words in Actor SSC_i + Object-of-Action SSC_i, unify them into one sentence of the structure: (Actor SSC_i +Action $SSC_i)_1$+(Actor SSC_i +Action $SSC_i)_2$+Object-of-Action SSC_i.
- When two consecutive phrases have the same Action SSC_i substitute in the second sentence this Action SSC_i by the corresponding "Generalized Action SSC_i."

5. Research and Development Perspectives for the Evaluations

The techniques introduced in this paper can be applied for a cluster of activities. All of them are unified by the focus of analysis rather unusual for the engineering endeavor. Cognisphere, Inc. calls these activities Meaning-Oriented Analysis of Text Sets (MOATS). "Texts" can be explained as narratives representing REALITY (i. e. *descriptions*). Before using constructively, the descriptions should be mapped into a different structure: an MR-Natural Language Text Architecture (MR-NLTA). This construction uses the following elements as its building blocks:

- natural language passages including "factual," generalized, labeling,
- numerical data (explicit, implicit, tabulated, etc.), sometimes with related interpretations
- formal logical constructions based upon standards and conventions related to a particular discipline, or domain of knowledge
- pictures and graphs with, or without related interpretations
- complex structures of presentation encompassing all of the above elements

Our familiarity with the existing research results allows us to be optimistic in our evaluation of the advantages of the proposed system. The existing competitors do not seem to be able to achieve results similar to those we can provide within the scope of our proposal, since they have not yet incorporated the multiresolutional technology of text processing.

Presently, there are no methods of testing for system of text processing with summarization and other, more sophisticated intelligent capabilities of processing. Both the formation of the test-set (of texts to be processed), and the methodology of testing, including the interpretation of the results, are obscure issues today. Most of the sources attribute the skill of summarization to the most intimate faculties of human intellect. "Which one of two summaries, prepared for the same text, is good and which one is not?" is the question we intend to answer as a part of the testing methodologies that will include the following directions.

Direction 1. Analysis of Meaning and Consistency

Both, summarization and abstracting answer an instantaneous need in newly generated documents with a pertinent (but not necessarily deep) meaning. In fact, the results of our text processing allow for expanding beyond the initial target to prepare a relevant compressed version, categorize it, and find a relevant list of keywords. Additional opportunities comprise:

a) Determining of Clusters of Meaning

After determining hierarchical networks of semantic fields, numerous clusters of them emerge which are more informative than it is required by the typical task of summarization.

b) Interpreting Additional Messages

These semantic fields contain island of additional meaningful "messages" conveyed by a text, or by a set of documents.

c) Recognition of Hidden Problems.

The lack of consistency in a semantic network at one or more levels of resolution speaks for the existence of hidden problems (in the text and/or in the real world described within this text).

d) Planning of Actions

Determining the course of actions, which can be recommended for dealing with the hidden (and recognized) problems.

Since all these operations are substantiated algorithmically, the numerical measure ("metric") can be introduced for judging the quality of results. If additional considerations can be introduced by human operators, they can be taken in account in formalizing the metric only if they cannot be incorporated into the algorithm.

Using these operation presumes a preliminary process of learning of the system functioning with parallel human based evaluation of results in a variety of situations.

Direction 2. Visual Support of Meaning

It is our observation, and it is part of the practice of decision-making organizations that both formal models and linguistic descriptions are not fully instrumental in conveying the meaning. Numerous additional issues and components of the meaning are illuminated when the decision-maker is given an opportunity to put together a visual representation for the meaning. We are not talking about graphs and other visual tools of supporting a presentation when numerical data are give, or qualitative results allow for some quantitative representation. We are talking about some intrinsic capabilities of the conceptual essence of MOATS.

The tools of text processing employed by MOATS allow for creation of visual images that have the same spatial and temporal structures as the soft model of the text has. The visual primitives are selected from the table of correspondence between the concepts and percepts (a tool seeking for syntactic and morphological resemblance between conceptual and perceptual units is under development). These visual primitives are being organized into a multigranular structure similar to the one extracted from the texts [4].

As a result, a report of the Mutual Funds Headquarters might be mapped into a visual image where in the midst of the multi-color ornament a several salient objects demonstrate some persistent (and predictable) motion: several polyhedra are quickly rolling around a deformed, oscillating egg-shaped body with a fuzzy contour. Visualization appeals to the intuitions of the decision-maker affecting his perception of the descriptive units of meaning obtained as a result of the prior analysis. It can be used for evaluation if interpretation tables are composed at the preliminary stage of situation learning.

Direction 3. Extraction and Analysis of Kindred Texts Packages

Analysis of large data-bases of text presumes browsing all documents, when the assignment is given to find a subset of them related to a particular issue. This issue is presumed to be represented not by the set of key-words and key-expressions but rather as a description of a particular situation. Even more challenging is a problem of extraction of subsets of kindred documents when the issue of interest is not specified but should be discovered. MOATS has all prerequisites required for solving this problem in the future.

Analysis of sets of kindred documents (articles related to each other) is performed as follows: documents are processed together (in parallel), and the meaning, hidden problems and inconsistencies are determined for the set as a whole.

These functions will include (but not bounded to) the following list of activities:

- creation of abstracts and lists of key-words for all kinds of written texts
- determining and interpretation of text statistics including

a) construction of Zipf's and Zipf-Mandelbrot's laws

b) finding statistics of parts of speech and phrases
c) computing N-grams

- composing lists of the natural language passages containing "facts," generalizations, labels , and other predetermined types of expressions
- extraction and organization of all available numerical data (explicit, implicit, tabulated, etc.)
- extraction of formal constructions based upon standards and conventions related to a particular discipline, or domain of knowledge
- development of abridged documents and compendiums
- development of pictures and graphs reflecting the abridged documents
- preparation of complex structures of presentation encompassing all of the above elements

Services based upon the MOATS system will take advantage of a possibility to interaction with the user. Thus, it will be possible to take into account both the goal of the user in its various aspects, and the variety of meanings that is (and/or possibly can be) conveyed by these texts as detected by the operator.

Certainly, the learning period is required when test text will be submitted to the system as well as the results of performance evaluation done by human operators (a representative statistics of operator evaluations is presumed). The learning cycle of the MOATS system contains the following components:

- receiving representative texts as input
- discussion with the user the required personalized features of the job assignment and the output form
- texts processing using both conventional and innovative techniques (described above)
- composing summaries, abstracts, surveys, compendiums, etc. fitting within preassigned specifications
- composing a list of keywords (the number of them can be preassigned)
- categorizing texts for both cases: with a preassigned classifier, or without it
- evaluating the results within a particular category by using the algorithmic "metric"
- evaluating the same results by a number of individuals considered experts in this particular category of meaning
- constructing an ontology terms database and monitoring its subsequent use for the user's needs; evaluating the ontologies algorithmically
- evaluating the same ontologies by a number of individuals considered experts in this particular category of meaning
- answering the user's questions concerning with the text and with the system's functioning; evaluating them by jurors and algorithmically
- formulating the meaning of the texts and hypothesize on its extension; evaluating them by jurors and algorithmically
- proposing explanations for the issues of interest; evaluating them by jurors and algorithmically
- discovering and explicating hidden problems within the world represented in the test set of texts and outlining the contradictions within these texts; judging the automated results
- constructing and regularly updating a knowledge base for a particular user; judging the automated results
- supplementing text processing with tools of visualization for enriching the results of interpretation and meaning analysis; helping the user in analysis of images
- outlining alternative actions for dealing with the problems and contradictions found in the text

As a service tool, MOATS processing is specialized to perform the above functions of evaluation regularly in response to the needs of a user and for verifying whether the tuning of the system has a favorable dynamics.

References

1. A. Meystel, *Semiotic Modeling and Situation Analysis: An Introduction*, AdRem, Bala Cynwyd, PA, 1995
2. A. Meystel, J. Albus, *Intelligent Systems: Architectures, Design, Control*, Wiley, NY 2001
3. A. Meystel, "Multiresolutional Representation and Behavior Generation: How Do They Affect the Performance of Intelligent Systems" (in this volume).
4. V. Grishin, A. Meystel, "Evaluation of System Intelligence Via Pictorial Data Visualization," Eds. A. Meystel, E. Messina, Measuring the Performance and Intelligence of Systems: Proceedings of the PERMIS'2000 Workshop, Gaithersburg, MD, August 14-16, 2000, pp. 533-540